How Do Personalized Recommendations Affect Consumer Explorations: A Field Experiment

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Abstract

Personalized recommendations are known for their ability to navigate shoppers to the most relevant products first, saving their time. However, the hidden cost is that shoppers are less likely to find other desirable products along the search process serendipitously. Such a potential cost casts doubts on whether websites should adopt personalized recommendations. I suggest a positive spillover effect of gained efficiency from personalized recommendations: consumers explore more because increased search efficiency countervails an increasing opportunity cost of time. In addition, total shopping time is expected to decrease because the new equilibrium marginal benefit of exploration is lower. I examine these hypotheses empirically using field experiment data from one of China’s biggest grocery delivery platforms. My findings are consistent with these hypotheses: consumers reduce search, spend more time exploring other categories and make more purchases while lowering their total shopping time. These findings are important because they show consumers active explorations under time pressure and they demonstrate a demand increasing mechanism of increasing search efficiency through personalized recommendations.

1 Introduction

E-commerce websites sell millions of products to consumers. To help consumers locate their preferred products, personalized recommendations, adopted by e-commerce websites, tailor products to consumers’ specific needs. By navigating consumers to their favored products, personalized recommendations save consumers’ time. A potential benefit of the saved time is that consumers can use it to engage in more directed explorations. However, the downside is that E-commerce websites might lose some profits from other products that consumers saw on the journey online. For instance, a consumer might check out items that she needs from the recommended list and leave the E-commerce website within a shorter time frame. On the contrary, suppose she had no recommendations, she might search on the website for her essential needs. During that search process, she might encounter other desirable products
that she did not expect to purchase without spending the extra time looking for the essentials. These kinds of serendipities bring consumers a pleasant shopping experience while generating revenue for the website. Hence, the trade-off between giving consumers personalized recommendations and allowing them to explore extensively becomes a practical problem for E-commerce websites to consider before adopting recommendations.

In this paper, I ask how do personalized recommendations affect consumer explorations on E-commerce websites. Specifically, I want to learn 1) whether personalized recommendations reduce consumer search of their favored products 2) does the increased search efficiency spillovers to more consumer exploration. I study the question in an online grocery setting where consumers shop for multiple products across various categories. This setting is typical because many large E-commerce websites such as Amazon, Taobao, and JD have consumers who come back frequently and purchase multiple products from different categories within one visit.

In the online shopping setting, I hypothesize that personalized recommendations reduce consumer search of their favored and frequently purchased products. Under time pressure, consumers have an increasing opportunity cost of time. The increased shopping efficiency will then counteract the increasing opportunity cost of time. Therefore, consumers will explore more in the less-frequently visit categories that they do not browse due to time pressure. However, the total shopping time is expected to reduce because recommendations only impact shopping efficiency without changing consumers’ expected benefit of further explorations. In that way, the new equilibrium marginal benefit of exploration will be lower as consumers spend more time on it. By the law of demand, the equilibrium quantity of time will be shorter.

I employ a first data set that contains an experimental variation on whether or not consumers observe personalized recommendations. The exogenous variation allows me to causally investigate the impact of recommendations on consumer shopping behaviors. I find that overall personalized recommendations reduce search measured by clicks yet increase demands. To delve into the changes, I distinguish the effect of recommendations on shopping behaviors in the following categories: frequently visit categories and rarely visit categories. I find that consumers spend proportionally more time exploring the infrequently visit categories and thus purchase more from them. The effect is also economically significant: treated consumers spend 24% more time in the less-frequently visit categories and order 35% more products from these categories. This finding is consistent with my first hypothesis, which predicts that recommendations lead to more consumer exploration. I then estimate the effect of recommendations on the total shopping time to test my second hypothesis. As expected, recommendations reduce the total shopping time, inferring that the efficiency improvement effect dominates any other potential learning effect. Meanwhile, consumers increase shopping frequencies, implying that they have a more pleasant shopping experience on the website under personalized recommendations. Furthermore, I explore personalized recommendations’ long-term impact by investigating consumers’ shopping behavior one month after the experimental period. I find that treated consumers tend to revisit more in the month after. They continue to spend time browsing and purchasing more from the infrequently visit categories explored in the experimental period. The economic magnitude of difference
persists: in the next month after the experiment ended, treatment users spend 7% more time in the explored categories and purchase 5% more items from there. This long-term effect suggests that consumers benefit from the extra explorations enabled by a higher search efficiency due to recommendations.

This paper makes the following two contributions. First, I demonstrate a demand increasing mechanism of increasing search efficiency through personalized recommendations. Specifically, I show that personalized recommendations make search more efficient in the frequently visit categories, which triggers more search in the less-frequently visit categories. This finding relieves the concern about losing additional profits from consumers’ unplanned spending. Indeed, I find that personalized recommendations free consumers’ time for more explorations capable of generating more revenue for the website. There have been concerns that recommendations’ growing usage can create a “filter bubble” (Pariser 2011[1]). However, the demonstrated benefit of consumers’ active explorations contradicts the “filter bubble” phenomenon, informing us that recommending familiar items will not always lead to consumption stagnation if exploration is a normal good. Therefore, E-commerce websites should exert more effort in developing their recommendations towards efficiency improvement.

Second, I document a new impact of recommendations on consumer engagement. In contrast to the point that recommendations can increase user engagement(Holtz et al. 2020 [2]), I find that personalized recommendations reduce total shopping time on the E-commerce websites through increasing shop frequency but meanwhile generate more revenue from increased consumer demands. In shopping circumstances, consumers not only search for inexperienced products that require an intensive search to learn match values, but they also spend time shopping for experienced products. Recommendations, therefore, serve mainly as the navigational role for experienced products and save shopping time. This contrast highlights the need for further studies of recommendations’ impact across various business contexts.

The rest of the paper is organized as follows. In the next session, I will review related work. Section 3 describes the empirical context and the experiment. In section 4, I will provide theoretical hypotheses based on my context and then show the data analysis and results. Section 5 concludes the paper and points out the direction for future research.

2 Related Literature

This paper relates to the literature on recommendation, particularly to work that examines the effect of recommendation on user behaviors. It is well documented in the literature that recommendations often lead to enhanced consumer engagement online(Freyne et al. 2009 [3], De et al.2010 [4]). In contrast, I find that better recommendations lead to less time spent on E-commerce websites. Another stream of papers explore the effect of recommendation on consumption diversity (Fleder and Hosanagar 2009 [5], Oestreicher-Singer and Sundararajan 2012[6],Holtz et al (2020) [2], Hosanagar et al. 2014[7], Nguyen et al. 2014 [8], Hervas-Drane 2015[9].) In particular, Holtz et al. (2020) [2] finds the trade-off impact in that personalized recommendation leads to higher consumer
engagement and but less diversity consumed. Our finding in the E-commerce context is quite the opposite. I show that personalized recommendations cause consumers to purchase more and spend more time searching for diverse categories without increasing their shopping time on the website. This contrast is mainly driven by the difference between online shopping recommendations versus content recommendations such as news, music, and movies. By studying the effect of recommendations in a prevalent but relatively understudied industry in the recommendation literature, I complement the understanding of recommendations' influence in our daily life.

By studying consumer search across many categories under the influence of recommendations, this study complements the search literature that focuses on the impact of rankings on consumer choices within one category. For example, Ursu 2018 [10] finds that on Expedia, a hotel booking website, ordered rankings decrease consumer search costs and increase the probability of a match with a seller, ultimately improving consumer welfare. Similarly, Ghose et al. (2014)[11], and De Los Santos and Koulayev (2017) [12] all looks at the effect of ranking within one specific category. I show that a multi-category search can exhibit some qualitative differences under the influence of ranking compared to the single-product search. Specifically, I have shown that saving consumers’ time in those familiar categories by a better ranking algorithm enables shoppers to discover desirable products in other less frequent visit categories. Therefore, my research complements the understanding of how a personalized algorithm can benefit consumers.

Furthermore, this paper also relates to research that discusses the impact of search frictions on consumers’ online shopping behavior. Ngwe et al. 2019 [13] find that increasing search frictions by placing discounted items lower in the list can cause higher average price sold and more purchases through inducing consumers to search for more products. This study discovers that removing search frictions by providing better recommendations can have a similar effect in that the increased search efficiency frees consumer time for more explorations.

This study is also related to work on optimal algorithms for ranking a set of options online. For example, Yoganarasimhan 2020[14] develops an algorithm to score the likely relevance of a search result to a consumer and rank according to the score. Ghose et al. 2014 [11] compare the effects of two ranking mechanisms in the lab and find that personalized ranking leads to more clicks but fewer purchases, probably due to information overload. De Los Santos and Koulayev (2017) [12] show that personalized ranking increases click-through rates based on model prediction. In contrast, I find that personalized ranking affects shopping efficiency rather than consumer expected utilities. As a result, personalized ranking leads to lower click-through rates and saves consumer time for more exploration and more purchases.

Lastly, given that I examine the impact of different product sorting strategies on consumer search behavior, this project is relevant to previous studies discussing product assortment strategies designed to trigger unplanned purchasing among consumers. For instance, Granbois 1968 [15] proposes placing popular product categories in scattered locations throughout the store, which is similar to the conventional wisdom of "hiding the milk at the back of the store" among practitioners. A more recent paper by Hui et al. 2013 [16] empirically finds a positive
impact of more distance traveled in-store on unplanned spending. However, critical aspects missing from these papers are consumer search costs and time pressure. In the offline setting, there is a fixed cost of physically entering the store. Still, the marginal cost of search is relatively low compared to the online environment because people cannot switch between shopping and other activities as freely as possible. Given that a consumer has entered the store, based on our model prediction, the consumer will stay longer in the store and explore more than the online setting. In that sense, hiding the milk at the back of the store is not necessary as the traditional practitioners would have done. Instead, I predict that if retailers provide a list of essential items at the front, consumers will voluntarily explore more in other store sections. Future research could study specific product assortment strategies that work for different contexts.

3 Background and Data

3.1 Online Grocery Industry

The online grocery industry has proliferated over the past ten years as online shopping becomes increasingly popular.\(^1\) In the U.S., firms like Amazon, Instacart, and Walmart accelerate the transition of offline to the online grocery business. Despite the extensive literature on studying consumer packaged goods and consumer shopping behavior at local grocery stores, research on online grocery shopping is sparse. Indeed, we are facing plenty of challenges and opportunities in the online grocery world. For instance, while offline grocery assortment varies little for each consumer who walks into the store within a day, online grocery stores can use algorithms to predict preferences and change product assortments based on specific consumer tastes instantly. However, we have limited knowledge of the effect of varying product listings based on consumer taste, which is critical for understanding the grocery business in the Internet age.

3.2 The Company and Empirical Background

I use data from a Chinese e-commerce platform that offers online sales and delivery of fresh produce. The company ran an experiment at the end of 2019 on its category page where consumers arrive to buy groceries by categories. Consumers usually arrive at the category page by selecting the specific category page, like walking down each aisle at a local grocery store. Or they can reach the category page by searching for specific keywords of a product name or a category name. The category pages display multiple brands or types of products within a category. In E-commerce, categories are usually classified into three levels. Take blueberry as an example; it belongs to category level one: fruit, category level two: berries, and category three: blueberry. I choose to focus on the highest category level, but my results are robust to the selection of category levels.

Figure 1 provides an example of shopping by categories on this website. I screenshot four different category

\(^1\)https://www.ibisworld.com/united-states/market-research-reports/online-grocery-sales-industry/
pages, including fruit, household supplies, snacks, and beverages on this website for illustration. The total number of such categories is 46, and the categorization did not vary for the entire experiment period. Consumers can click on each item on the page to go to the product detail pages or directly add it into their cart. The purchases are made at the checkout page.

3.3 Experiment

The field experiment happened from December 10 to December 16, a week at the end of 2019. Consumers are randomly selected into the treatment group with access to recommendations and the control group that cannot see recommendations. The experiment happens at the consumer level, so these consumers stay in the same group during the entire experimental period. After December 16, the personalized ranking algorithm was widely rolled out to all consumers who arrive at the website’s category pages. The experiment aimed to compare personalized ranking versus non-personalized ranking.

Figure 2 presents how the control and treatment groups see differently on their screens. In particular, treatment group users observe products ranked by predicted CTRs that use consumer-specific viewing and purchase history features. Examples of these features include `user_sku_click_number` that signifies the number of items this user has clicked on the product (SKU), `user_sku_exposure_number` that means how many times the user has been exposed to this product, `user_cid3_buy_count` that indicates how many products the user has bought from the specific category level three. By using these features, the ranking algorithm can recommend products based on a user’s preference for a product. The taste is predicted from the machine learning model that the company adopts, which is not publishable. But intuitively, those products that are browsed clicked, or purchased by consumers before should come up higher on the list in a personalized ranking. In terms of new products, if a new product shares some features with the products that consumers prefer will be ranked higher than other new products. For
instance, a price-sensitive consumer is more likely to see a low price new wine ranked higher than other expensive new wine. For new users, the personalized ranking algorithm takes real-time data into account. Real-time data can be any history (browse, click, add-cart, and purchase) a consumer had with the product before arriving at the category page. Since the category page is not the first stop after consumers open the App, this kind of history is highly likely to exist for new users. For control group users, they see products ranked by product popularity and availability. An analogy on other E-commerce websites could be sorting by "Most Popular" and "Most Relevant.” The difference here is that users are randomly assigned to these two groups.

The total number of participants in the experiments is 1,114,199 who arrive at the category page from Dec 9th to Dec 16th, 2019. 83% of users are randomly assigned to the control group, and 17% of users are in the treatment group. ²

3.4 Data

I have data on consumer conversion on the website, product id, product category information, and an identifier of which group this consumer belongs to (Treatment versus Control). Conversion data includes browsing, click, add to cart, and purchase. A consumer browses a product refers to the exposure of that product to a consumer. Whenever the product appears on the consumer’s visiting page, it is counted as one exposure. Browsing history is a more precise measure for consumer attention on the website. When a consumer is not paying attention when logging on to the website, the exposure will stay the same, whereas the time count will increase. ³ A consumer click

²The company decided to run an experiment on fewer people so that in the case when the new intervention is not too detrimental to the overall revenue if it is not profitable. Though I have a one to five ratios of treatment versus control experiment rather than a one-to-one ratio experiment, the fewer proportion of treatment users only negatively impact the experiment’s statistical power. Given that I have enough observations, it is less of a concern.

³Browse data is also widely used for measuring consumer attention rather than the actual timestamp in the industry according to my data source.
is counted when she clicks on the product, which leads her to the product detail page where she will see detailed descriptions of the product. A consumer can either add the product directly to her cart from the category page without going into the detail page; this behavior is recorded as a direct add to cart. If she adds the product to her shopping cart from the detail page, it will be documented as an add cart on the detail page. In my sample, an add cart means the consumer adds the item into her cart from the category page. Lastly, a purchase happens at the checkout page after the product is added to the cart.

Table 1 provides summary statistics of the key outcome measures in the sample. The outcome variables are scaled to protect data privacy. The key takeaway from this table is that some outcome variables are skewed, like purchases and revenue. This phenomenon is common in E-commerce data. Hence, I use log transformation to take care of this issue in the later data analysis. However, the zero-inflation problem is less severe in the data because the 75th percentile of purchase and revenue variables are already bigger than zero. The boxplots of these variables are shown in Appendix 7.3. The plots are more direct ways to witness that zero-inflation is less of a concern in this data.

In addition to the experiment week data, I also observe consumer conversion data from a week before and a month after the experiment ends. The previous week's data is used for identifying consumer’s browsing history. Namely, I define those products exposed to a specific consumer in the prior week as repeat-browse products; similar definitions apply for repeat-add-cart items and repeat-purchased items. The post-experiment data is used to study how likely consumers will continue to purchase from those explored categories.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Pctl(25)</th>
<th>Median</th>
<th>Pctl(75)</th>
</tr>
</thead>
<tbody>
<tr>
<td>browse</td>
<td>2,266.759</td>
<td>3,890.596</td>
<td>3.700</td>
<td>281.200</td>
<td>943.500</td>
<td>2,641.800</td>
</tr>
<tr>
<td>click</td>
<td>11.380</td>
<td>23.274</td>
<td>0.000</td>
<td>0.000</td>
<td>3.700</td>
<td>11.100</td>
</tr>
<tr>
<td>add_cart</td>
<td>14.289</td>
<td>24.244</td>
<td>0.000</td>
<td>0.000</td>
<td>3.700</td>
<td>18.500</td>
</tr>
<tr>
<td>purchase</td>
<td>7.742</td>
<td>16.050</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>11.100</td>
</tr>
<tr>
<td>revenue</td>
<td>74.512</td>
<td>165.594</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>94.128</td>
</tr>
</tbody>
</table>

Variables are scaled by an unrevealed number to preserve data privacy.

4 Result

4.1 Hypothesis

First, I want to list two hypotheses regarding the impact of recommendations on consumers to guide the empirical data analysis. I hypothesize that personalized recommendations reduce consumer search. The increased shopping efficiency counteracts the increasing opportunity cost of time. Therefore, consumers will explore more in the less-frequently visit categories that they do not usually spend time browsing or purchasing. Intuitively, this makes

\footnote{Appendix 7.1 includes a theoretical model that fits my empirical setting and mathematically derives two hypotheses.}
sense because the marginal cost of time is still lower than the continuation value of search when consumers stop earlier after shopping more efficiently from the recommended list. To give a concrete example, suppose on a given shopping trip, a consumer planned for an hour for that trip. With the help of recommendations, she can finish within 20 minutes compared to the usual 30 minutes spent on shopping for frequently-purchased groceries. At the 20 minute cutoff, her continuation value, which is the expected benefit from further exploration, is likely to be higher than her opportunity cost of time. She will have more time left and thus explore for a longer period of time given she has already paid fixed cost entering the store.

Next, I expect total shopping time to decrease when recommendations only impact shopping efficiency without changing consumers’ expected benefit of further explorations. An economic explanation is that as consumers allocate proportionally more time on exploration, which brings utility to consumers, the new equilibrium marginal benefit/cost is going to end at a lower point. By the law of demand/supply, the new equilibrium time will decrease. In short, the effect of recommendations is mainly saving time on buying necessities, which leaves more time for exploration. It does not change the overall expectation of the utility gained from exploration. Thus, the increase in the exploration time will not exceed the reduction in the necessity shopping time, which nets to a reduction in the total shopping time.

4.2 Empirical Analysis

Given the above two hypotheses, I conduct data analysis to estimate the impact of recommendations on consumer search. I quantify the effect of personalized recommendations by estimating the following log-linear regression.

\[
\log(1 + y_i) = \beta_0 + \beta_1 T_i + \epsilon_i
\]

where \(T_i\) is an indicator of the individual \(i\) being in the treatment group. The primary focus is on the sign and the magnitude of the coefficient \(\beta_1\). \(\beta_1\) informs us about the average treatment effect of personalized ranking on various outcome variables. Moreover, \(\beta_1\) is interpreted as the relative increase/decrease compared to the control group users who do not see the intervention. The outcome measures are aggregated over the week of the experiment for each individual, so it is a cross-sectional regression.
4.3 Effect on Search and Demand

First of all, I examine the main experiment effect on the number of items that consumers click, add cart, purchase, and the website’s total revenue. Table 2 shows the regression results of the main experiment effect. From left to right, each column reports regression results on outcome measures, including the number of items clicked, the number of add cart items, the number of items purchased by each individual, and the total revenue generated from an individual consumer. The first row shows the regression coefficients estimates $\beta_1$, and the second row displays the percentage changes at the average level of $y$ in the Control group.

In short, I find that personalization reduces search, but it also leads to an increase in demands. Specifically, compared to the control group users, treated users make fewer clicks. On average, they click on 1.29% (statistically significant at 5% level) fewer items than the control group users who do not have personalized ranking. However, they add 8.12% more things into their cart directly from the category page. From their expanded carts, consumers also purchase 5.97% more items. In turn, the website generates, on average, 5.64% more revenue from the treatment group than the control group.

The fact that consumers purchase more and the revenue increases without more clicks can be driven by either the reminder effect or the exploration effect. To be specific, on the one hand, it is possible that personalized recommendations remind consumers to buy things that they would have forgotten. Alternatively, personalized recommendations might enable consumers to find desirable products through exploration, which generates extra revenue website. In the next sections, I will examine the impact of personalized recommendations on explorations. In particular, given that personalized recommendations increase shopping efficiency in general, I want to test the hypothesis that increased search efficiency will spillover to more explorations, mostly in the less frequently visit

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5. I use log$(1 + y)$ because of the skewed distribution of outcome variables. $(1 + y)$ transformation allows me to take care of zero issues in the outcome variables.

6. Appendix 7.2 displays 1000 bootstraps of mean distributions of outcome measures for each group, Treatment and Control. I multiply the data by an unrevealed number to protect data privacy. So the absolute values of outcome measures do not matter as long as the mean distribution is normal. Though these variables are skewed, their means are confirmed to distribute normally. Also, the mean difference between the two groups is distributed normally. These histograms justify the mean comparison between treatment and control groups.

7. Due to confidentiality concern, I am only allowed to display relative changes instead of absolute measures. The upside of relative changes is that they are straightforward numbers to tell the economic significance.

8. In this way, I avoid the complication from time variations. Given that the experiment happens at the individual level, it makes sense to aggregate the analysis at the individual level.
categories. Furthermore, I will test the hypothesis that personalized recommendations reduce overall shopping time on the website, which helps me distinguish between the mechanism of learning versus pure efficiency gain from recommendations.

### 4.4 Effect on Exploration

First of all, I define exploration as time spent on those less frequently visit categories instead of products. So I am studying consumers’ consumption expansion into other categories, not just products. The reason is that the experiment happens on the category page, where consumers shop by categories. Generally, items are more likely to be substitutes within a certain category, \(^9\). The way that personalized ranking tends to rank relevant products on the top will create negative externality to lower-ranked substitutes. \(^10\) For example, if a consumer sees her favorite milk listed on the top of the dairy section, she will probably add the top ones into her cart without paying extra effort searching for other brands of milk. To avoid such externalities between products, I decide to examine shopping behavior across more independent categories, which gives us a clearer picture of how recommendations affect consumer search. \(^11\)

Table 3 presents evidence of consumer explorations in the less-frequently visit categories. Firstly, infrequent visit categories in my data context mean that consumer has not browsed them a week before the experiment period. \(^12\) These infrequent visit categories are heterogeneous among consumers in that consumers have different shopping patterns. Columns in Table 3 report how many items that consumers spend time searching, click, add cart, or purchase are from the infrequently visit categories. \(^13\) \(^14\) In general, I find that consumers spend only a small fraction of time exploring. The third row in Table 3 reports the average baseline level of exploration among the control users. For example, control group consumers, only spend 1.66% of total time on exploring new category items. They only distribute 0.7% of clicks on new category items and add 0.6% into their carts. Overall they only purchase 0.5% of things from newly explored categories. In terms of treatment users, they spend more time in those infrequent visit categories as they browse 23.75% (on top of a baseline level of 1.66%) more items. Meanwhile, treated consumers tend to distribute a larger proportion (19.3% more on top of the baseline average) of clicks on these categories. They also add 34.83% more things into their carts than control users from these new categories and make 34.8% more new purchases in the end. In aggregate, I can conclude from this evidence that I find the economically and statistically significant effect of exploration in the infrequent visit categories after efficiency

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\(^9\)In Robustness Check section, I also examine explorations within categories that tend to exhibit variety-seeking features

\(^10\)Previous paper has found that such a ranking leads to inadequate screening in that consumers are less likely to consider low-position items. (Derakhshan et al 2018 [17])

\(^11\)Similarly, Ursu and Dayabura 2019 [18] examines consumers’ search costs of shopping across multiple independent categories to study retailers’ strategy to allocate these categories optimally given consumers’ search costs.

\(^12\)I removed new consumers from both groups as they do not have prior history on the website. Therefore, the number of observations is smaller.

\(^13\)I construct a proxy for total shopping time, which is the total number of items browsed on the entire website during the experiment period. As I discussed before, I do not observe the exact timestamp of consumers’ footprints on the website. But the number of items browsed is a good proxy for time measure as consumers get exposure to all sorts of objects when they spend time actively browsing on the website.

\(^14\)I assign zero values for this measure if a user makes zero-click/add to cart/order on the items that she browsed.
improvement from shopping in the familiar categories.

Table 3: Proportional Exploration in Newly Discovered Categories

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>fr_new_category_time</td>
<td>fr_new_category_click</td>
<td>fr_new_category_cart</td>
<td>fr_new_category_order</td>
</tr>
<tr>
<td>( t )</td>
<td>0.00387***</td>
<td>0.00137***</td>
<td>0.00226***</td>
<td>0.00168***</td>
</tr>
<tr>
<td>( % ) change</td>
<td>23.75%</td>
<td>19.30%</td>
<td>34.83%</td>
<td>34.80%</td>
</tr>
<tr>
<td>Baseline Average</td>
<td>0.0166</td>
<td>0.0071</td>
<td>0.0065</td>
<td>0.0049</td>
</tr>
<tr>
<td>( N )</td>
<td>984489</td>
<td>984489</td>
<td>984489</td>
<td>984489</td>
</tr>
</tbody>
</table>

* \( t \) statistics in parentheses
* * \( p < 0.10, ** p < 0.05, *** p < 0.01 \)
Dependent variables are \( \log(1+Y) \) transformed
The average level of exploration in the baseline group is shown in the third row
I remove new users without history, so the number of observation is fewer than the total population

4.5 Effect on Total Shopping Time

This section investigates the effect of personalized recommendation on the total shopping time consumers spend on the website. As the second hypothesis predicts, if we expect personalization only mechanically vary the time allocation between frequent visit categories and infrequent visit categories, total shopping time will reduce. Alternatively, if consumers change their perception of the website due to a better recommendation, I will observe an increase in the total shopping time spent on the website. Based on the results reported in Table 4, I find that personalized recommendations reduce total shopping time in each visit by 0.35%. This effect is statistically significant at the 5% level, but the economic magnitude is minimal, which implies that consumers do not change too much in spending time online after personalization.

Given that consumers spend a bit less time on the website, I am curious to increase visit frequencies due to recommendations. I look at revisits paid over the experiment period to measure how often consumers return to the website after personalization is adopted. Regarding the effect on revisits, the personalized recommendation group revisits the website more often, at a rate of 0.24% more than the non-personalized group users. Again, this is a statistically significant effect, but the magnitude is not enormous because the absolute average number of this measure is already a number between 1 and 7. Overall, the regression results in Table 4 confirm that personalized recommendations save time for consumers but do not vary their perception about other infrequent visit categories. The increase in revisits and demand per visit is positive news for websites that adopt personalization. The negative impact on the shopping time is not too perturbing if websites care more about enhancing revenue per minute spent on the website.
### Table 4: Effect on Total Shopping Time and Visits

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>time_per_visit</td>
<td>n_visits</td>
</tr>
<tr>
<td>t</td>
<td>-0.00351 (-1.15)</td>
<td>0.00242** (2.19)</td>
</tr>
<tr>
<td>% change</td>
<td>-0.35%</td>
<td>0.24%</td>
</tr>
<tr>
<td>N</td>
<td>1114203</td>
<td>1114203</td>
</tr>
</tbody>
</table>

\[ t \] statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Dependent variables are log(1+Y) transformed

### 4.6 Long Term Effect

In this section, I want to examine if the effect of personalized recommendation persists over a more extended time than just a week. The website rolled out the personalized ranking to all consumers who arrive at the category page after the experiment ended. Therefore, the estimates in the following regressions are lower-bounds estimates. I choose a month after the experiment ends to investigate the long-run effect because the pandemic hit the Chinese market after Jan 16th, 2020, when the data about online grocery shopping became less credible because there were large amounts of stockpiling behavior happened.

### Table 5: Effect on Total Shopping Time and Visits

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>churn</td>
<td>revisit_next_month</td>
</tr>
<tr>
<td>t</td>
<td>-0.00133 (-1.63)</td>
<td>0.00665*** (3.14)</td>
</tr>
<tr>
<td>% change</td>
<td>-0.56%</td>
<td>0.83%</td>
</tr>
<tr>
<td>N</td>
<td>1114849</td>
<td>1114849</td>
</tr>
</tbody>
</table>

\[ t \] statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Dependent variables are log(1+Y) transformed

First of all, I want to examine if consumers continue to shop frequently on the website in the next month. I construct two measures to examine the revisits reported in Table 5. I first look at the churn rate for the two groups of people. If a user stops coming to the website in the next month, then churn will be equal to 1 for that user and vice versa. In terms of churn rate, I do not find any significant difference between the two groups. In other words, I do not find that personalized recommendation leads to fewer or more churns. Next, I examine how many days a user visits the website within the next month. I find that treated consumers continue to shop more frequently on the website than the control users who did not see personalized ranking before. The magnitude of difference between the two groups is 1.11% percent more, which is a lower bound effect. In the counterfactual world where the experiment did not end, I expect a larger revisit rate difference.

Next, I would like to analyze if those newly explored categories continue to draw attention from consumers. One alternative scenario could be that those discoveries are just one-time serendipities in that consumers find them
unattractive after exploration and thus stop wasting time or money on them. If that is the case, exploration does not seem beneficial for consumers or the website in the long run. Nevertheless, I find that consumers continue to explore and purchase from these newly explored categories. Table 6 reflects this pattern. I investigate whether or not consumers continue to spend time, click, and buy from these newly explored categories. Treated users spend 7.28% more time browsing in the newly explored category afterward. They also click on 6.49% more items from these categories. Moreover, they add 6.42% more items into the cart and purchase 5.14% more items from these categories in the month after. These results suggest that using the extra time saved by recommendations, consumers are more likely to discover desirable products that they tend to purchase in the long term.

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>fr_new_category_time</td>
<td>fr_new_category_click</td>
<td>fr_new_category_cart</td>
<td>fr_new_category_order</td>
</tr>
<tr>
<td>t</td>
<td>0.00814***</td>
<td>0.00662***</td>
<td>0.00803***</td>
</tr>
<tr>
<td></td>
<td>(17.13)</td>
<td>(13.93)</td>
<td>(16.80)</td>
</tr>
<tr>
<td>% change</td>
<td>7.28%</td>
<td>6.49%</td>
<td>6.42%</td>
</tr>
<tr>
<td>N</td>
<td>755379</td>
<td>755379</td>
<td>755379</td>
</tr>
</tbody>
</table>

Table 6: Long Run Exploration in Newly Discovered Categories

5 Robustness Check

5.1 Alternative Mechanisms

5.1.1 Potential Retention Effect

Section 4.5 shows that treated consumers pay slightly more visits to the websites than control group consumers. An alternative explanation for the exploration effect found in section 4.4 could be that treated consumers disproportionately purchase more new items in their extra visits to the websites. If that is the case, the mechanism that recommendations increase shop efficiencies and induce more explorations does not hold anymore.

To check whether the above explanation exists, I examine the fraction of new items only in the first order that consumers placed on the website since the experiment started. What’s more, I check the interaction term between indicator T and the order occasion within the experiment’s week. The interaction term’s coefficient tells us whether the fraction of new items per order increases with the order occasions within a week.

\[ fr_{new\_purchase\_per\_order_i} = \beta_0 + \beta_1 T_i + \beta_2 T_i \times order\_occasion + \epsilon_i \]

Table 7 reports the regression results. The first column shows the fraction of new items in the first order that the consumers placed on the website after the experiment. Even in the first order, consumers are already showing
exploration patterns as they purchase more new items.

The second column shows the exploration effect across different order occasions. The coefficient of interest $\beta_2$ before the interaction term $T_i \times \text{order\_occasion}$ is not significant, implying that treated consumers do not systematically vary their explorations across multiple orders placed on the website.

Table 7: Robustness Check: Exploration Effect Across Multiple Orders

<table>
<thead>
<tr>
<th></th>
<th>(1) fr_new_purchase_first_order</th>
<th>(2) fr_new_purchase_per_order</th>
</tr>
</thead>
<tbody>
<tr>
<td>t</td>
<td>0.00173***</td>
<td>0.000852</td>
</tr>
<tr>
<td></td>
<td>(8.95)</td>
<td>(1.46)</td>
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<tr>
<td>n_order</td>
<td>0.00497***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(24.18)</td>
<td></td>
</tr>
<tr>
<td>tn_order</td>
<td>0.000830*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.72)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>397930</td>
<td>488673</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Dependent variables are log$(1+Y)$ transformed

The first column shows the first order new purchase fraction and the second columns shows the interaction effect model

5.1.2 Potential Learning Effect

Another plausible effect from better recommendations could be that consumers change their overall perceptions of the website and explore categories that the website is less famous for. For instance, before recommendations, this website may be renowned for its fresh produce. After observing the recommended lists, a consumer might change her prior belief about this website only selling good fresh produce. She might spend some time exploring other less popular categories, like household supplies on the same website, instead of visiting different places for household supplies. To investigate if this phenomenon exists, I compared the most popular ten categories on the website with the most popular ten explored categories by treated users to see if there is any difference.

15
Figure 3: Most Popular Categories
5.2 Within Category Exploration

Other than exploration in less-frequently visit categories, I expect to see exploration happens in the category where consumers tend to seek varieties. Among the 46 first-level categories, I summarize the average number of different purchased products by each individual within a category. I define variety-seeking categories in terms of how many different products consumers purchase. According to the definition, I found the following categories that contain the largest variety of products purchased: fruits, snacks, hotpot, and snacks.

Table 8-11 presents the regression of the fraction of new items consumers click, add cart, and purchase within a specific category. Overall, I find that consumers purchase more new items within the category that they commonly seek variety. However, I find that more purchases of new things do not come together with more search for new items. Instead, consumers directly add new items to their carts and experiment with them. Therefore, I find that consumers tend to seek variety by directly ordering new things within the fruit, snack, hotpot, and snack sections.

Table 8: Within Category Exploration Effect - Fruit

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log_fr_new_click</td>
<td>-0.00965***</td>
<td>0.0114***</td>
<td>0.00556***</td>
</tr>
<tr>
<td>t</td>
<td>(-10.52)</td>
<td>(12.48)</td>
<td>(7.12)</td>
</tr>
<tr>
<td>% Change</td>
<td>-3.59%</td>
<td>4.31%</td>
<td>3.23%</td>
</tr>
<tr>
<td>N</td>
<td>931728</td>
<td>931728</td>
<td>931728</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 9: Within Category Exploration Effect - Veggie

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log_fr_new_click</td>
<td>-0.00536***</td>
<td>0.0148***</td>
<td>0.0102***</td>
</tr>
<tr>
<td>t</td>
<td>(-4.88)</td>
<td>(12.78)</td>
<td>(9.52)</td>
</tr>
<tr>
<td>% Change</td>
<td>-2.18%</td>
<td>4.88%</td>
<td>4.55%</td>
</tr>
<tr>
<td>N</td>
<td>615072</td>
<td>615072</td>
<td>615072</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 10: Exploration Effect - Hot Pot

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log_fr_new_click</td>
<td>0.00102</td>
<td>0.0169***</td>
<td>0.0112***</td>
</tr>
<tr>
<td>t</td>
<td>(0.99)</td>
<td>(15.36)</td>
<td>(11.69)</td>
</tr>
<tr>
<td>% Change</td>
<td>0.50%</td>
<td>6.98%</td>
<td>6.56%</td>
</tr>
<tr>
<td>N</td>
<td>624448</td>
<td>624448</td>
<td>624448</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01
Table 11: Within Category Exploration Effect - Snack

<table>
<thead>
<tr>
<th>log_fr_new_click</th>
<th>log_fr_new_cart</th>
<th>log_fr_new_order</th>
</tr>
</thead>
<tbody>
<tr>
<td>t</td>
<td>t</td>
<td>t</td>
</tr>
<tr>
<td>0.00339**</td>
<td>0.0196***</td>
<td>0.0146***</td>
</tr>
<tr>
<td>(2.22)</td>
<td>(12.83)</td>
<td>(11.02)</td>
</tr>
<tr>
<td>% Change</td>
<td>% Change</td>
<td>% Change</td>
</tr>
<tr>
<td>1.50%</td>
<td>8.90%</td>
<td>9.52%</td>
</tr>
<tr>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>314062</td>
<td>314062</td>
<td>314062</td>
</tr>
</tbody>
</table>

* t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

5.3 Randomization Check

I want to examine if users are similar on pre-experiment observable characteristics, specifically conversion behaviors. I compare the conversion behavior between Treatment users and Control users a month before the experiment happened. I test that the experiment groups are balanced on these pre-experiment conversion variables. Table 12 shows the result of these tests, and I find that I cannot reject the hypothesis that these groups are balanced.

Table 12: Randomization Checks for Balance on Outcome Measures

<table>
<thead>
<tr>
<th>Avg_T</th>
<th>Std.dev_T</th>
<th>Avg_C</th>
<th>Std.dev_C</th>
<th>p-value*</th>
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</thead>
<tbody>
<tr>
<td>0.30</td>
<td>0.31</td>
<td>0.30</td>
<td>0.30</td>
<td>0.65</td>
</tr>
<tr>
<td>0.03</td>
<td>-0.13</td>
<td>0.03</td>
<td>0.03</td>
<td>0.41</td>
</tr>
<tr>
<td>0.03</td>
<td>-0.24</td>
<td>0.03</td>
<td>0.03</td>
<td>0.77</td>
</tr>
<tr>
<td>0.04</td>
<td>-0.13</td>
<td>0.04</td>
<td>0.04</td>
<td>0.14</td>
</tr>
<tr>
<td>0.61</td>
<td>0.64</td>
<td>0.61</td>
<td>0.65</td>
<td>0.24</td>
</tr>
</tbody>
</table>

* Averages and Standard Deviations are log transformed by an unrevealed base to preserve the confidentiality of the data
* N = 106,901 for Treatment and 536,745 for Control
* For each variable, p-values are from a two-sided t-test for equality of means between Treatment and Control groups.

6 Conclusion

In this paper, I study how do personalized recommendations affect consumer exploration. I explore this question in the online shopping context where multi-category shopping and repeat purchases are frequent. I construct a theoretical model to motivate my empirical analysis. Then I employ a first data set with an experimental variation on personalized recommendations to causally evaluate its impact. I find that personalized recommendations reduce consumer search but increase consumer demand and the website’s revenue. Moreover, I find evidence consistent with my hypothesis, which predicts that increased search efficiency will spillover to more consumer explorations. Specifically, consumers who have personalized recommendations spend more time in less-frequently visit categories and purchase more products from them. The increase in exploration time does not fully compensate for the saved time in the frequently visit categories; hence, consumers’ total shopping time decreases slightly. These results suggest that personalized recommendations mainly increase consumer shopping efficiency without varying their
expected benefit of searching. Regarding consumer satisfaction, I find that personalized recommendations cause consumers to revisit more often to the website. Lastly, consumers enjoy their discoveries in that they continue to browse and purchase from these explored categories afterward.

In general, this paper’s findings demonstrate a new demand increasing mechanism of increasing search efficiency through personalized recommendations. This study’s results inform us that by leveraging recommendations’ navigational roles, E-commerce websites can achieve higher revenue from consumers’ explorations that expand their demands. The “filter bubble” effect of recommendations is less of a concern given that consumers are actively discovering outside of the recommended options.

Besides, our research suggests that saving shopping time for essential goods is another way to increase unplanned spending in the grocery setting. The finding contrasts with the traditional belief of "hiding the milk at the back of the store" among offline grocery store practitioners. In the offline environment, there is a fixed cost of physically entering the store. Still, the marginal search cost is relatively low compared to the online setting because people cannot switch between shopping and other activities as freely as possible. Given that a consumer has entered the store, based on our model prediction, the consumer will stay longer in the store and explore more than the online setting. In that sense, hiding the milk at the back of the store is not that necessary. Instead, I predict that if offline grocery stores can provide a list of essential items at the front, consumers will voluntarily explore more in other store sections.

This research points to fruitful directions for further research. First, I have focused on the influence of recommendations on one E-commerce website. Due to data limitation, I cannot investigate whether the expanded demand on one retailer cannibalizes another retailer’s demand. From the retailer’s perspective, an increase in the current visit demands is favored because it safeguards the retailer from losing the purchase to a competitor. Further research should also consider the effect of recommendations on store choice decisions and competitions between different stores.

Finally, further research could explore the extent to which the model and the results from this paper generalize to offline grocery stores and other retail environments. As I predicted above, it is plausible that consumers will explore further in the offline setting even though they have what they need in their basket soon after they walk into the store. Researchers can study the impact of displaying essential products at the front instead of hiding them at the back of the offline store and track consumers’ shopping path around the store to see if they continue exploration. Or researchers could look for data from other retail environments where repeat purchase is less frequent than the online grocery context, like Amazon and Taobao, to examine the impact of recommendations on consumer explorations. These studies will further complement the understanding of recommendations’ effects and allow retailers to optimize their marketing strategies.
7 Appendix

7.1 A Theoretical Model

I present a simple theoretical model that conceptually fit my empirical context. This model yields several empirically testable implications that help guide and interpret my empirical analysis. Our model fits in the context where consumers go on an E-commerce website to shop for multiple products coming from various categories within one trip. Examples of these E-commerce websites can be Amazon, Taobao, JD.com and various other large online stores. Categories of consumers’ basket of goods can be divided into frequently visit categories and less frequently visit categories. Frequently visit categories are those that were browsed before in the past week, whereas infrequent browsing categories are those that were not browsed by a certain consumer in the past week.

7.1.1 Model

The utility of searching for each consumer $i$ is

$$U_i = B_i - C_i$$

where

$$B_i = f(x_i)$$

and

$$C_i = g(x_i + y_i)$$

Here, I define $x_i$ as time spent on exploring in less frequent browsing categories on the website, $y_i$ as time spent on frequent browsing categories on the website.

$f(.)$ is a strictly concave function as we assume marginal benefit of searching is decreasing as consumer spend more time exploring. ($f''(.) < 0$) This insight comes from the seminal paper in sequential search literature: Weitzman 1979[19]. His sequential search model informs us that as one search more, the possibility that the next item will exceeds the current reservation value is lower. Furthermore, I assume that time spent on shopping for familiar items does not bring additional benefit because consumers know the match value with those frequent browsing items.

Then I model the total opportunity cost of searching as a convex function due to increasing marginal cost of searching. The increasing marginal search cost arises from the notion that consumers have to leave at some point instead of staying online for an infinite amount of time. Hence, $g(.)$ is a strictly convex function, which implies $g''(.) > 0$. The cost of searching is a function of both time spent on exploration $x_i$ and purchasing familiar items $y_i$, hence the total time spent on the website.
Since $U_i$ is a concave function of $(x_i, y_i)$, there exists a pair of $(x_i, y_i)$ that maximizes $U_i$. The equilibrium pair of $(x_0, y_0)$ that maximizes $U_i$ satisfies the condition that

$$F(x_0, y_0) = f'(x_0) - g'(x_0 + y_0) = 0 \quad (1)$$

Theoretically, I first want to know if the time spent on exploration increases as the time for buying familiar items is saved by using a personalized recommendation. Mathematically, I want to know how does changes in $y_i$ affect changes in $x_i$, so I examine the first difference of $x_i$ on $y_i$.

**Hypothesis 1: If time spent on buying familiar products reduces, exploration time will increase.**

**Proof:**

By implicit function theorem, we can differentiate both sides of equation (5) with respect to $y$, which gives us

$$0 = \frac{\partial F(x_0, y_0)}{\partial y} + \frac{\partial F(x_0, y_0)}{\partial x} \frac{dx}{dy} \quad (2)$$

$$= -g''(x_0 + y_0) + (f''(x_0) - g''(x_0 + y_0)) \frac{dx}{dy} \quad (3)$$

Rearranging equation (2) gives us

$$\frac{dx}{dy} = \frac{g''(x_0 + y_0) > 0}{(f''(x_0) - g''(x_0 + y_0)) < 0} < 0 \quad (4)$$

Therefore, $x$ is a decreasing function of $y$, which implies that as time spent on buying from familiar categories $y$ decreases, time spent on exploration $x$ will increase.

This occurs because the comparative static: $\frac{dx}{dy}$ is less than zero, which implies that time spent on exploration is a decreasing function of time spent on shopping for familiar products.

Intuitively, this makes sense because the marginal cost of time is still lower than the continuation value of search when consumers stop earlier after shopping more efficiently from the recommended list. To give a concrete example, suppose on a given shopping trip, a consumer planned for an hour for that trip. With the help of recommendations, she is able to finish within 20 minutes compared to the usual 30 minutes spent on shopping for frequent purchase groceries. At the 20 minute cutoff, her continuation value which is the expected benefit from further exploration is likely to be higher than her marginal cost of time. So she will have more time left for exploration.

Next, I would like to know if total shopping time vary with the change in $y_i$ caused by personalized recommendation. Mathematically, that question is transferred to as how does change in $y_i$ affect change in $y_i + x_i$. Intuitively, this is hard to see because if $y_i$ decreases, $x_i$ will increase, but the net change in $y_i + x_i$ is hard to tell as one term rises and the other one drops.

**Hypothesis 2: Overall shopping time will decrease as a result of increased efficiency for buying familiar items.**

**Proof:**
Rewrite (5) as a function of time spent on exploration $x$ and total time spent online $u = x + y$

$$F(x_0, u_0) = f'(x_0) - g'(u_0) = 0 \quad (5)$$

By implicit function theorem, we can differentiate both sides of equation (5) with respect to $y$, which gives us

$$0 = \frac{\partial F(x_0, u_0)}{\partial y} + \frac{\partial F(x_0, u_0)}{\partial x} \frac{dx}{dy} + \frac{\partial F(x_0, u_0)}{\partial u} \frac{du}{dy} \quad (6)$$

$$= f''(x_0) \frac{dx}{dy} - g''(u_0) \frac{du}{dy} \quad (7)$$

Rearranging equation (6) gives us

$$\frac{du}{dy} = \frac{f''(x_0) \frac{dx}{dy}}{g''(u_0)} > 0 > 0 \quad (8)$$

Therefore, $u$ is an increasing function of $y$, which implies that as time spent on buying from familiar categories $y$ decreases, time spent on the website $u$ will increase.

The more intuitive explanation is that as consumer allocate proportionally more time on exploration which brings utility to consumers, the new equilibrium marginal benefit/cost is going to end at a lower point. Thus, the new equilibrium time will decrease. In short, the effect of recommendations is mainly saving the time on buying necessities, leaving more time for exploration. It does not change the overall expectation about the utility gained from exploration. Thus, the increase in the exploration time will not exceed the reduction in the necessity shopping time, which nets to a reduction in the total shopping time.

### 7.2 Mean Distributions of Outcome Measures

These histograms justify the mean comparison between treatment and control groups. Appendix 7.2 displays 1000 bootstraps of mean distributions of outcome measures for each group, Treatment and Control\(^{15}\). Though these variables are skewed, their means are distributed normally, as it is shown in the bootstrap distributions below. Meanwhile, the mean differences between the two groups are also distributed normally.

\(^{15}\)The true mean of outcome variables cannot be revealed here. All outcome variables are multiplied by an unrevealed number to protect the data privacy.
7.3 Boxplots of Outcome Measures
References


